

Unraveling the recruitment problem: A review of environmentally-informed forecasting and management strategy evaluation

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ABSTRACT

Studies describing and hypothesizing the impact of climate change and environmental processes on vital rates of fish stocks are increasing in frequency, and concomitant with that is interest in incorporating these processes in fish stock assessments and forecasting models. Previous research suggests that including environmental drivers of fish recruitment in forecasting is of limited value, concluding that forecasting improvements are minimal while potential spurious relationships were sufficient to advise against inclusion. This review evaluates progress in implementing environmental factors in stock-recruitment projections and Management Strategy Evaluations (MSEs), from the year 2000 through 2017, by reviewing studies that incorporate environmental processes into recruitment forecasting, full-cycle MSEs, or simulations investigating harvest control rules. The only successes identified were for species with a short pre-recruit survival window (e.g., opportunistic life-history strategy), where the abbreviated life-span made it easier to identify one or a limited set of key drivers that directly impact dynamics. Autoregressive methods appeared to perform as well, if not better, for species with a longer pre-recruit survival window (e.g., seasonal, inter-annual) during which the environment could potentially exert influence. This review suggests that the inclusion of environmental drivers into assessments and forecasting is most likely to be successful for species with short pre-recruit survival windows (e.g., squid, sardine) and for those that have bottlenecks in their life history during which the environment can exert a well-defined pressure (e.g., anadromous fishes, those reliant on nursery areas). The effects of environment may be more complicated and variable for species with a longer pre-recruit survival window, reducing the ability to quantify environment-recruitment relationships. Species with more complex early life histories and longer pre-recruit survival windows would benefit from future research that focuses on relevant species-specific spatio-temporal scales to improve mechanistic understanding of abiotic-biotic interactions.

1. Introduction

Interest in incorporating environmental processes in fish stock assessments and forecasting models is increasing in step with studies describing and hypothesizing impacts of climate change and environmental drivers on vital rates of fishes. However, much of the research on the importance of environmental factors in the design of management procedures found that including environmental indices in

recruitment forecasting models results in little or no improvement with respect to fishery management performance. This lack of improvement is largely based on research related to gadoid-like life histories. More specifically, since 1999, thirty eight studies have cited Basson (1999), which we consider to be a benchmark analysis on the topic of using environmental factors for short-term recruitment predictions for a gadoid-like life history. This incongruity makes it difficult to justify calls for increased complexity that potentially increase risk without

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increasing benefits.

In this study we highlight the simulation study of Basson (1999) and then trace developments in the two decades since its publication. Basson (1999) found no benefits to either stock conservation or average yield from including an environmental factor in a stock assessment model. Furthermore, reductions in fishery management uncertainty took place only given a strong environment-recruitment relationship. Basson (1999) recommended that future work explicitly incorporate the assessment procedure within the simulation framework and that the stock-recruit relationship be refitted during every assessment, both with and without environmental factors. A more general recommendation was to explore additional life histories to determine which may benefit from inclusion of environmental covariates in stock assessment models.

The implicit nature of the relationship assumed between the environmental driver and recruitment, and the linkage with the harvest strategy, may have contributed to the negative result in Basson's study. For example, Basson (1999) modeled a gadoid-like periodic life history, based largely on the strong negative relationship between Irish Sea cod, *Gadus morhua* (ICES sub-area 7a; ICES, 1999), age-0 recruitment and sea-surface temperature (SST; Planque and Fox, 1998). Drinkwater (2005) also predicted a reduction in Irish Sea cod recruitment with increased SST with climate change. Planque and Fox (1998) hypothesized several mechanisms to explain how warmer water might lower recruitment, such as decreased fecundity, negative effects on egg or larval physiology, or food availability. The most important effect of the gadoid life history was likely on the simulated management strategy, where higher predicted temperatures, implying lower recruitment, dictated a lower fishing mortality (F) reference point and subsequent total allowable catch (TAC) for that year. Recruits (age-0) were not available to the fishery until age one, so setting a lower TAC during a year of poorer environmental conditions would not have an immediate effect on fishing mortality on recruits from that year. However, temperature was similar in consecutive years because of modelled autocorrelation in the time series, so the TAC set during the next year would also be relatively low, relieving some pressure on the previous year's recruits. The overall effect of the management tactic on Basson's performance measures, yield and spawning stock biomass (SSB), was delayed and indirect because age-1 fish made up a small proportion of the catch and were not fully mature until age 3. These management tactics might be more effective for stocks that matured earlier, had higher natural mortality, or grew more quickly, with more of the spawning biomass at younger ages. An alternative management approach would be to delay the implementation of stricter TACs to more closely match the timing of the entry into the fishery for cohorts spawned during years of poor environment. This approach might be more effective at lower stock sizes and at a steeper part of the stock-recruit relationship because reduced mortality on spawning age classes should have a stronger positive effect on recruitment. Basson (1999) does not report the parameter values for the stock-recruit curve used, but when analyzing the same data, Planque and Fox (1998) found recruitment to be essentially independent of SSB.

In reviewing the work that has built upon Basson (1999), we use the term 'recruitment' to designate the single age class at the end of the interval where population dynamics are governed by a stock-recruit function. In this case, the stock-recruit function generally models the early-stage mortality prior to recruitment as being density-dependent, whereas the mortality rates of individuals older than the recruitment age are typically modeled as being density-independent. We distinguish this use of 'recruitment' from earlier definitions where it was defined as the age when fish become fully vulnerable to the fishery (Ricker, 1954, 1975). In contemporary stock assessment models, vulnerability to fishing gear at all ages can be directly modeled as part of the assessment, as either a function of size or age, and potential temporal changes in vulnerability can be accommodated as well (Quinn and Deriso, 1999). Thus, the recruitment definition that we adopt places the emphasis on processes that exert influence on survival between spawning

and the resultant recruits, rather than focusing on older, fully vulnerable ages where survival is less likely to be influenced by the environment and more likely to vary with fishing pressure.

Since Basson (1999), the inclusion of environmental variables in fisheries assessments remains rare. A recent examination of 1250 assessments worldwide identified only 24 that included ecosystem information regarding stock productivity, of which 14 were environmental factors (Skern-Mauritzen et al., 2016). However, a review with a wider scope, which summarized the use of all ecosystem information used in stock assessments in the U.S. rather than just recruitment, found that 24% of all U.S. stock assessments included ecosystem information (Marshall et al., 2018). Since Basson (1999), several studies have made recruitment forecasts (e.g., Ward et al., 2014), some of which include environmental drivers. Most likely, the combination of life-history traits and management tactics will affect the utility of environmentally based recruitment forecasting. We undertook a review of literature from the year 2000 through 2017, to evaluate progress in implementing environmental factors in Management Strategy Evaluations (MSEs) and stock-recruitment forecasts. We identified over sixty peer-reviewed studies that address questions of environmentally-driven recruitment forecasting and related MSEs. Just over one-third of these studies were found to be relevant during initial screening, where relevance was determined as a study going beyond mere correlation to model an environmental driver explicitly or implicitly and the stock assessment and/or management implications were considered. The relevant studies we consider below are broadly categorized as either primarily focused on recruitment forecasting or else on simulations of full-cycle MSEs or harvest control rules (HCRs; Table 1).

The goals of this review are 1) to examine successes and challenges across studies that include environmental considerations in MSEs or stock recruitment forecasts and 2) to highlight study characteristics that result in different outcomes. This review is loosely structured by topics related to how the relevant studies address or fulfill issues raised in, or recommended by, Basson (1999). Basson's main recommendations included: 1) the consideration of a wide range of life-history types, exploitation patterns, and stock-recruitment relationships, 2) identification of strong interactions between environmental drivers and recruitment, 3) increased prediction skill for environmental factors, 4) increased realism with respect to management actions and implementation, and 5) the consideration of long-term trends in environmental time series. Section 2 reviews studies across a wide range of different stock-specific life histories or general scenarios. Section 3 reviews the need for simulation and forecasting studies with more realistic assessment, harvest, and management implementation modules. Section 4 summarizes the use of a) either univariate or multivariate mechanistic drivers, b) historical data, c) spatial scale, and d) temporal forecast scale. Finally, sections 5, 6, and 7 provide a synthesis of successes, challenges, and future research recommendations to improve relevance to fisheries management.

2. Life-history strategies and environmentally-informed recruitment forecasts

2.1. Characterizing life histories

The variability in life-history strategies across fish taxa and among ecoregions results in differences in the duration and abundance of individuals in defined stages (Houde, 2002) (Fig. 1). Several authors have tried to classify and quantify differences in life history with respect to implications for fishery management (e.g., Winemiller and Rose, 1992; King and McFarlane, 2003; Winemiller, 2005). However, the classifications of periodic, opportunistic, (Winemiller and Rose, 1992; Winemiller, 2005) (Fig. 2) and salmonid (McCann and Shuter, 1997) life histories are used to structure our review of the varied responses to environmentally-driven recruitment processes.

Periodic strategists, such as many groundfish species, are

Table 1
Summary of reviewed studies. Previous data analyses typically informed MSE studies with theoretical recruitment-environment relationships.

	Publication	Spatial scale	Life history Type, Genus (Classification)	Species	Mechanistic relationship?	> 25 Years Data	Forecast Length	Includes temperature metric?	Includes large spatial scale drivers?	Captures environmental uncertainty?
Forecasting	Burke et al., 2013	Northeast Pacific	Salmon, <i>Oncorhynchus</i> (Salmonid)	Chinook salmon	Yes	No, 2000-2010	Annual	Yes	Yes	No
	Deyle et al., 2013	California Current	Coastal Pelagic, <i>Clupea</i> (Opportunistic)	Pacific sardine	No	Yes	Near-term	Yes	Yes	No
	Haeseker et al., 2005	Northeast Pacific	Salmon, <i>Oncorhynchus</i> (Salmonid)	Pink salmon	Yes	Yes, 1950-1996	Annual	Yes	No	No
	Hare et al., 2010	U.S. mid-Atlantic region	Groundfish, <i>Micropogonias</i> (Opportunistic)	Atlantic croaker	Yes	Yes, 1900-2007	Long-term, 2008-2100	Yes	No	No
	ICES, 2013	Norwegian and Barents Sea	Coastal Pelagic, <i>Clupea</i> (Opportunistic)	Spring Spawning Herring (NSSH)	Yes	Yes		Yes	No	No
	Logerwell et al., 2003	Oregon and Washington, USA	Salmon, <i>Oncorhynchus</i> (salmonid)	Coho salmon	Yes	Yes, 1969-2000	Annual	Yes	Yes	No
	Mackenzie et al., 2008	Washington, USA	Coastal Pelagic, <i>Sprattus</i> (Opportunistic)	Sprat	Yes	Yes, 1955-1999	Near-term, 1 to 5 years	Yes	Yes	No
	Mackenzie et al., 2012	Baltic Sea	Coastal Pelagic, <i>Sprattus</i> (Opportunistic)	Sprat	Yes	Yes, 1974-2005 and 1960-2009	Long-term, 2006-2100	Yes	No	Yes
	Mueter et al., 2011	Eastern Bering Sea	Groundfish, <i>Gadus</i> (Periodic)	Walleye Pollock	Yes	Yes, 1979-2008	Long-term, 2009-2050	Yes	No	Yes
	Rupp et al., 2012	Oregon, US	Salmon, <i>Oncorhynchus</i> (Salmonid)	Coho Salmon	Yes	Yes, 1970-2009	Annual	Yes	Yes	No
	Pacific Fishery Management Council (PFMC), 2018	Oregon, US	Salmon, <i>Oncorhynchus</i> (Salmonid)	Coho Salmon	No	Yes, 1952-2017	Annual	Yes	Yes	No
	Vaughan et al., 2011	Northern U.S. Gulf of Mexico	Coastal Pelagic, <i>Brevoortia</i> (Opportunistic)	Gulf Menhaden	Yes	Yes, 41 (recruit), 46 (environment)	Annual	No	No	No
	Ward et al., 2014	General	General	General	NA	Yes	NA	NA	NA	NA
	Wertheimer et al., 2017	Southeast Alaska, US	Salmon, <i>Oncorhynchus</i> (Salmonid)	Pink salmon	No	No, 1997-2015	Annual	Yes	Yes	No
	Wilderbuer et al., 2013	Eastern Bering Sea	Flatfish, <i>Hippoglossoides</i> , <i>Lepidopsetta</i> , <i>Atheresthes</i> (Periodic)	Flathead Sole, Northern Rock sole, Arrowtooth Flounder	Yes	Yes	Long-term, 2001-2050	Yes	Yes	No
	Winship et al., 2015	Central California	Salmon, <i>Oncorhynchus</i> (Salmonid)	Chinook Salmon	Yes	Yes, 1983-2012	Annual	Yes	No	No
	Agnew et al., 2002	Falkland Islands	Invertebrate, Teuthida (Opportunistic)	Squid (<i>Loligo gahi</i>)	No	No, 1987-2000	In Season	Yes	No	No
	A'mar et al., 2009a	Gulf Of Alaska	Groundfish, <i>Gadus</i> (Periodic)	Walleye Pollock	Theoretical	Yes, 1961-2004	Long-term, 50 years	NA	NA	Yes
	A'mar et al., 2009b	Gulf Of Alaska	Groundfish, <i>Gadus</i> (Periodic)	Walleye Pollock	Yes	Yes, 1962-2005	Long-term, 2006-2050	Yes	No	Yes
MSE / Simulation/ Reference Points / HCRs	Brooks, 2013	General	Flatfish	General	NA	NA	NA	NA	NA	NA
	Brunel et al., 2010	North Sea	Coastal Pelagic, Groundfish, <i>Clupea</i> , <i>Gadus</i> , <i>Pleuronectes</i> (Opportunistic and Periodic)	Herring, Cod, Plaice	No	Yes, 1963-2006 (Cod)	Long-term, 50 years	Yes	Yes	Yes
	Haltuch and Punt, 2011	General	Groundfish, <i>Eopsetta</i> , <i>Merluccius</i> , <i>Sebastes</i> (Periodic)	Generalized Flatfish, Hake, Rockfish	Theoretical	Yes, 25 and 50 years	Long-term, 25 and 50 years	NA	NA	Yes
	Hurtado et al., 2010	California Current	Coastal Pelagic, <i>Sardinops</i> (Opportunistic)	Sardine	Theoretical	Yes, 1976-2006	Long-term	Yes	No	Yes
	Ianelli et al., 2011	Eastern Bering Sea	Groundfish, <i>Gadus</i> (Periodic)	Walleye Pollock	Yes	Yes, 1963-2008		Yes	No	Yes

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Table 1 (continued)

Publication	Spatial scale	Life history Type, Genus (Classification)	Species	Mechanistic relationship?	> 25 Years Data	Forecast Length	Includes temperature metric?	Includes large spatial scale drivers?	Captures environmental uncertainty?
Punt, 2011	California Current	Rockfish, <i>Sebastes</i> (Periodic)	Pacific Ocean Perch	Theoretical	Yes, 1956–2006	Long-term, 2010–2050	No	No	Yes
Punt et al., 2013	Australia	Invertebrate, <i>Parulirus</i> (Equilibrium)	Rock lobster	Theoretical	Yes, 1951–2010	Long-term, 80 years	NA	NA	Yes
Punt et al., 2014	Eastern Bering Sea / Alutian Islands	Invertebrate, <i>Paralithodes</i> , <i>Chionoecetes</i> , <i>Lithodes</i> (Equilibrium/Periodic)	Multiple Alaska Crab Stocks	Theoretical	Yes, ~1968–1978	Long-term, 2011–2050	NA	NA	NA
Skagen et al., 2013 Szuwalski and Punt, 2012	General Eastern Bering Sea	Groundfish, <i>Gadus</i> (Periodic) Invertebrate, <i>Chionoecetes</i> (Equilibrium/Periodic)	Generalized Gadid Snow crab	Theoretical Yes	NA Yes, 1978–2010	NA Long-term, 50 years	Yes NA	NA NA	NA Yes

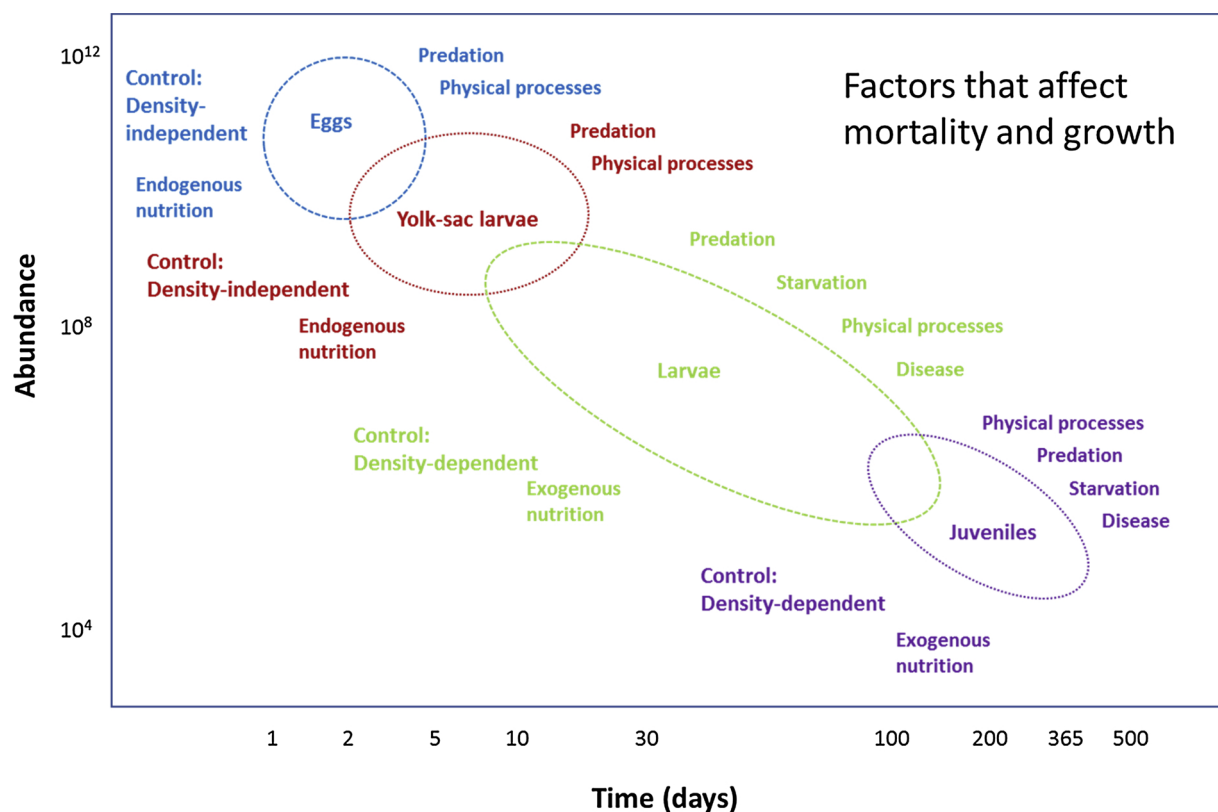
characterized as slow growing, long-lived, and highly fecund species that have evolved to persist in highly variable environments with periodic recruitment success (Winemiller and Rose, 1993). Opportunistic strategists, such as many coastal pelagic species, are characterized as fast growing, short-lived, with intermediate fecundity. Salmonid strategists, such as Atlantic and Pacific salmon, are characterized by intermediate body size, age at maturity, and egg size, as well as having shorter life spans, fast growth, and low fecundity (King and McFarlane, 2003).

Each life-history strategy can exhibit a number of biological transitions corresponding to distinct stages, and generally, the duration of each successive life stage increases as a fish develops. The influence of environmental factors such as temperature, salinity, prey levels, and predation are expected to play important roles during different stages of development. First, the timing of spawning or egg production is often linked to environmental conditions or cues, with differing responses between spawning strategy. For example, the total annual eggs to be spawned are fixed prior to the spawning event for determinate spawners, whereas eggs can develop at any time during the spawning season for indeterminate spawners. These two strategies confer different advantages and vulnerabilities depending on the distribution of favorable environmental conditions expected during the spawning season. Likewise, there is a gradient of environmental influence related to spawning type (Balon, 1975), e.g., substratum type and condition will influence benthic spawners, oceanographic conditions will affect broadcast pelagic spawners, and environmental effects may be less influential for eggs of species with parental care or live birth. Variability in environmental conditions can influence egg and larval development rates (e.g., Pepin, 1991), which in turn, through stage duration (see Leggett and DeBlois, 1994), leads to variable mortality rates. Environmental conditions can also influence juvenile growth rates and therefore mortality rates (Rice et al., 1993; Houde, 1997). At the juvenile stage, important factors include whether the nursery grounds separate juveniles from adults and if those areas are limited in extent, which can lead to density dependent mortality (Beck et al., 2001; Bogstad et al., 2016).

2.2. Periodic strategists

Walleye pollock (*Theragra chalcogramma*), a gadid and periodic strategist, has long been a research focus. Spring wind and water temperature are thought to influence larval survival, and fall temperature and predator abundance are thought to mediate age-0 survival, affecting recruitment (Ciannelli et al., 2004). Mueter et al. (2011) used these mechanistic relationships to explain substantial variation in stock-recruit model residuals and developed a model to make long-term recruitment forecasts (2010–2050) based on Intergovernmental Panel on Climate Change (IPCC) climate model output. Results suggest that recruitment, spawner biomass, and catch would likely decline over the coming decades, compared with forecasts assuming random recruitment.

While there is a good mechanistic understanding of environmental factors that drive walleye pollock recruitment, MSEs suggested that management strategies incorporating regime shifts resulted in lower precision, higher bias, and mismatches between the levels of catch and productivity (A'mar et al., 2009a). The current management strategy, without an environmental linkage, outperformed strategies incorporating regime shifts in productivity because the overall risk of overfishing during periods of stock decline was lower. In later work, A'mar et al. (2009b) found that management strategies incorporating environment often exceeded historical catch levels because management did not respond quickly to declining productivity, thus increasing the risk of overfishing. The authors postulated that the management strategy might be improved when fluctuations or trends in stock productivity occur by using a fishery control rule with a fixed lower limit for spawning biomass, at which point fishing would be restricted or



Redrawn from Houde (1987, 2002)

Fig. 1. Intrinsic versus extrinsic factors that drive differences in the duration and abundance of individuals at defined stages.

eliminated if the model estimated spawning biomass declines below this limit.

Ianelli et al. (2011) used IPCC climate projections across a range of scenarios that incorporate warming SSTs to evaluate alternative management strategies for the Eastern Bering Sea walleye pollock stock. Outcomes from climate-based stock projections resulted in lower catch and declining biomass due to reduced recruitment compared to projections based on the current management scenario and strategies that

used a constant recruitment relationship. If future recruitment remains similar to past recruitments, then both status quo management, with static reference points and current ecosystem considerations, and the climate-based alternatives, perform similarly. There is no gain in management performance using climate-based reference points. However, if warming conditions result in reduced recruitment, then the status quo management results in lower average catches and an increased likelihood of fishery closures. The climate-based reference

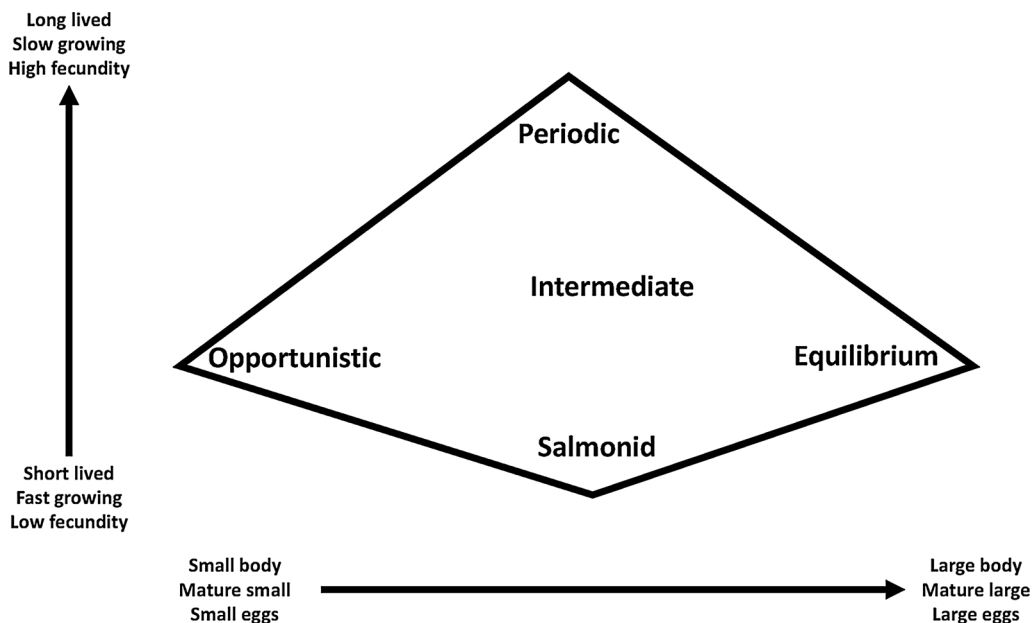


Fig. 2. Four end point life history strategies, with a fifth intermediate strategy in the center. Adapted from a principal components plot from King and McFarlane (2003, Fig. 1). The five points corresponding to each strategy were placed at the approximate center of each cluster of species from King and McFarlane's figure. Note that in King and McFarlane's (2003) original figure, the labels for opportunistic and periodic strategists were inadvertently switched, but have been placed correctly in the current figure.

points and control rules track the decline in productivity, allowing the target stock size to shift lower with declining recruitment resulting in higher fishery catches and fewer fishery closures.

Research on North Sea cod, (*Gadus morhua*) a periodic gadid, by Kell et al. (2005) evaluated the effect of including climate impacts on short- and long-term management strategies. Results suggest a small effect of climate on short-term stock recovery, which was more dependent on fishing effort reductions and that incorporating climate into stock assessment projections did not lead to an improvement. However, over the long-term, climate had a greater effect, although reducing fishing mortality still resulted in higher catches and stock size.

Investigations of the inclusion of several environmental variables into stock-recruit models for three Eastern Bering Sea periodic flatfish species (northern rock sole, *Lepidopsetta polyxystra*; flathead sole, *Hippoglossoides elassodon*; and arrowtooth flounder, *Atheresthes stomias*) found that springtime wind pattern was important for predicting recruitment for all three species (Wilderbuer et al., 2013). The authors hypothesized that winds acting to transport pelagic larvae to favorable nursery grounds were responsible for above-average recruitment. However, the Arctic oscillation was a more important recruitment predictor for arrowtooth flounder, which the authors hypothesized might be due to effects on larval survival through settlement patterns. Recruitment forecasts using environmentally modified stock-recruit relationships coupled with IPCC climate model predictions were used to produce 40-year forecasts, though comparable forecasts excluding environmental effects were not completed.

Winter mortality of estuarine-dependent juveniles has a strong effect on Atlantic croaker (*Micropogonias undulatus*) recruitment (Hare et al., 2010). Cold air temperatures can result in cooling estuarine water temperatures to critically low levels in nursery areas, leading to high mortality of overwintering age-0 croaker and reduced recruitment. Hare et al. (2010) found that inclusion of minimum winter air temperature in the stock-recruitment model resulted in a significantly better fit to the stock-recruit data. This temperature-dependent stock-recruit model produced recruitment predictions that were generally consistent with the stock assessment. Long-term recruitment forecasts incorporating IPCC climate model temperature predictions showed increases in recruitment concurrent with warmer, milder winters (Hare et al., 2010).

Work on two periodic strategists (Atlantic cod, *Gadus morhua*, and European plaice, *Pleuronectes platessa*) and one opportunist (Atlantic herring, *Clupea harengus*) by Brunel et al. (2010) echoed the findings of Basson (1999); the gain from incorporating environmental factors into the management strategy was dependent on the strength of the environment-recruitment relationship. Marginal improvements in management performance were found given the inclusion of environmental factors, with the most improvement under unfavorable environmental conditions. The authors suggest that moving beyond use of recent historical data to include forecasted environmental data might improve outcomes, but this is hindered by difficulty of making reliable oceanographic forecasts. Historical observations may not fully capture future conditions adequately under climate change and it is unknown whether current environment-recruitment relationships will remain stationary into the future.

Using a simulation model parameterized for three different life-history types (i.e., long-lived and unproductive, moderately long-lived and productive, and short-lived and variable production), Haltuch and Punt (2011) provide further reason for caution when incorporating apparent environment-recruitment relationships into forecasts. They often found false detections (i.e., Type-I error) given a correlation between a periodic environmental index and recruitment, for all three life-history types. Failure to detect true correlations (i.e., Type-II error) was also common; however, results varied depending on the length of the simulated time series and the assessment method applied. Type-II errors were more problematic for the long-lived periodic rockfish (canary rockfish, *Sebastes pinniger*) than for the periodic flatfish (petrale

sole, *Eopsetta jordani*) and opportunistic North Pacific hake (*Merluccius productus*) examples. This work suggests that applying the wrong environmental relationship may actually make recruitment forecasts worse. Haltuch and Punt (2011) suggested that criteria for including environment-recruitment relationships within a management framework could include 1) the use of an *a priori* conceptual mechanistic model based on environmental data at spatial and temporal scales that make biological sense, 2) clearly explaining the extent of data dredging (Burnham and Anderson, 2002), 3) using data-reduction techniques (e.g., principal component analysis) to produce a smaller number of potentially more informative indices, and 4) using the most parsimonious model that explains a high proportion of the variability in the data (Guisan et al., 2002).

Evaluating harvest strategies for a slow-growing, low-productivity, periodic species (Pacific ocean perch, *Sebastes alutus*), Punt (2011) incorporated different delays in the spring transition period as predicted under global warming scenarios. Stock rebuilding was affected by forecasts of spring transition, but the impact could be reduced if the target *F* was allowed to adapt during the rebuilding. However, rebuilding time did not improve when including the correct form of the environment-stock-recruit relationship. Instead, the current management system was responsive to climate-induced changes in biological parameters despite not being included explicitly in the operating model or projections.

A slightly different approach was used by Skagen et al. (2013) on a hypothetical periodic species, where trends in environmental factors forced changes in all biological parameters that might be affected (e.g., growth, condition, weight, maturity, and recruitment). Incentives to increase or decrease the total allowable catch were implemented, in addition to the current management tactics. However, the authors found that using only environmentally-driven processes to inform management decisions (indicator based management) was not sufficient. Stock assessment estimates of stock status were also needed, and without that information the environmental indicator was an insufficient basis for sustainable management decisions. The authors express caution at generalizing this result too broadly however, as their primary intent was to illustrate a simulation framework.

2.3. Opportunistic strategists

Research on two small pelagic opportunistic species, sprat (*Sprattus sprattus*) and sardine (*Sardinops sagax*), found water temperature to be an important predictor of recruitment. Studies of Baltic Sea sprat (MacKenzie et al., 2008; MacKenzie et al., 2012) cite several earlier papers demonstrating effects of water temperature on survival of eggs and larvae (see citations in MacKenzie et al., 2008). Earlier work shows that recruitment of sprat can be predicted by incorporating SST into models (MacKenzie and Köster, 2004). One-year recruitment forecasts including low predicted SST are substantially lower than forecasts ignoring the environment (MacKenzie et al., 2008).

SST was found to influence Pacific sardine recruitment via spatial shifts in the distribution of age-1 recruits during warmer years that results in increased availability to fisheries (Jacobson and MacCall, 1995). Later, SST was incorporated into a temperature-based HCR for Pacific sardine (Hill et al., 2011). Re-evaluation of the SST relationship indicated a lack of improved recruitment predictions (McClatchie et al., 2010), but recent work suggests SST remains important (Jacobson and McClatchie, 2013) and that SST impacts on recruitment vary, depending on population size (Deyle et al., 2013). In fact, including SST, or a proxy, improved short-term sardine forecast skill by about 30% (Deyle et al., 2013). Given the persistent influence of SST for Pacific sardine recruitment, Tommasi et al. (2017a) used a MSE to compare the performance of harvest policies that either included or excluded seasonal SST forecasts. The harvest policy that incorporated both stock biomass and skillful SST predictions led to increases in stock biomass and catch and reductions in the probability of catch and biomass falling

below socioeconomic or ecologically acceptable levels (Tommasi et al., 2017a). However, they recommended combining the SST informed harvest policy with additional catch restrictions at low stock sizes to buffer against SST forecast errors. While work on Pacific sardine has focused on temperature-dependent harvest policies, SST-recruitment relationships have been used to produce long-term (90 years) recruitment forecasts for another sardine stock that estimated increased spawning biomass due to increasing SST (MacKenzie et al., 2012).

Vaughan et al. (2011) found that recruitment forecasts of age-0.5 Gulf menhaden (*Brevoortia patronus*), a small pelagic estuarine-dependent clupeiform, are improved using discharge from the Mississippi River. Early observations (Govoni, 1997) led to the hypothesis that greater river discharge hinders the movement of Gulf menhaden larvae from the continental shelf spawning areas into estuarine nursery areas. One-year recruitment forecasts dependent on river discharge always contained the observed recruitment within the 95% confidence intervals in each year of an eight-year retrospective analysis (Vaughan et al., 2011).

Incorporating environment into MSEs for opportunistic species is likely to be useful because the recruiting year class is a large proportion of the total stock size. Agnew et al. (2002) investigated whether incorporating SST six months prior to Falkland squid (*Loligo gahi*) recruitment could improve single-cohort fishery management. The mechanistic link between SST and Falkland squid recruitment is unknown but likely related to growth rates. Using SST predictions to set fishing mortality resulted in increased catch and lower risk of early fishery closure, but fishing mortality varied widely unless the amount of change in catch was limited.

Hurtado-Ferro et al. (2010) conducted an MSE for Japanese sardine (*Sardinops melanostictus*), where reference points changed at an environmental threshold. The authors found marginal improvements in outcomes for long-term management strategies, along with no benefit for short-term management strategies. Hurtado-Ferro et al. (2010) argued that good environmental predictions are not needed for management of this fishery; simply knowing the environmental threshold at which a new management strategy should be implemented was enough.

2.4. Salmonid strategists (Pacific Salmonids)

The first months at sea for Pacific salmon are considered a critical period during which recruitment may be determined (Beamish and Mahnken, 2001; Wells et al., 2012; Kilduff et al., 2014a, b; Woodson and Litvin, 2015). Following Percy (1992), researchers focusing on Pacific salmon have attempted to link oceanographic conditions during or near the time of out-migration (juveniles migrating from fresh to saltwater) to early survival and later recruitment. For salmon populations from Alaska through California, Hare et al. (1999) and Mantua et al. (1997) demonstrated the impact basin-scale factors can have on influencing salmon recruitment. Roughly, Northeast Pacific Ocean temperatures are inversely related to production of salmon in the California Current but positively associated with production of salmon from Alaska. Mechanically, these relationships are the result of a generally upwelling-dominated system in California Current and a downwelling system in Alaska (Hare et al., 1999; Mantua et al., 1997). Unfortunately, while informative, the relationships between production of salmon and solely basin-scale dynamics have proven too coarse to reliably forecast population-specific salmon recruitment. Wells et al. (2016) provides a mechanistic understanding of the relationships between the basin-, regional-, and meso-scale environment and survival of a single central California Chinook salmon (*Oncorhynchus tshawytscha*) population. Namely, the strength and location of the North Pacific High pressure cell in winter relates to late-winter upwelling along the California coast which provides nutrients to the system and sets potential productivity in spring as salmon out-migrate (Logerwell et al., 2003). As spring approaches, regional upwelling and transport dynamics determine the productivity and retention of salmon prey items (Schroeder

et al., 2014). If salmon prey items are not available, salmon survival, growth and condition of salmon are reduced and salmon predators may switch to preying on smaller, poor condition salmon juveniles (Tucker et al., 2016). Such spatially restricted dynamics and life-history bottlenecks, e.g., ocean entry point, suggest that a well-defined mechanistic conceptual model could lead to improved forecasts for Pacific salmon populations.

A large body of research has been dedicated to improving Pacific salmon forecast models in the largely bottom-up driven California Current (Checkley and Barth, 2009). Burke et al. (2013) examined the value of incorporating environmental variables identified in previous process studies (ranging from local conditions and ecosystem processes to large-scale oceanographic and atmospheric variables) into the Columbia River Chinook salmon adult forecast of returns, finding that a forecast model fit retrospective abundance data well. Using a similar range of local and large-scale environmental drivers, Rupp et al. (2012) and Logerwell et al. (2003) successfully fit environmental data to time-series of Oregon coho salmon (*Oncorhynchus kisutch*) recruitment. Process studies for Atlantic salmon (*Salmo salar*) are also demonstrating clear connections between environmental conditions and recruitment (e.g., Mills et al., 2013). These examples explicitly consider the bottom-up determinants of the productivity of the shelf ecosystem and suggest successful forecasting of salmon recruitment is possible. However, the effect of bottom-up determinants on survival is neither direct nor linear (Wells et al., 2017). Rather, when production on the shelf is reduced and the forage taxa are less available, predators can switch from preferred prey to salmon near shore, imparting significant variability in recruitment (Emmett et al., 2006; Wells et al., 2017). Such significant cascading effects related to bottom-up drivers can reduce the value of using environmental covariates in forecast models.

For example, although Pacific salmon have a clear life-history bottleneck, analyses by Winship et al. (2015) were unable to identify reliable environmental covariates for improving the prediction of adult abundance from sibling models (i.e., estimating remaining cohort abundance at sea from the abundance of younger, jack, salmon returns). Forecasts of Sacramento River, California fall-run Chinook salmon adult abundance have been effectively estimated from the abundance of returning jacks (Pacific Fishery Management Council (PFMC, 2018), but this relationship has weakened (Winship et al., 2015). Regression models incorporating different temporal combinations of eight environmental variables, 20 in total considering seasonal investigations, related to maturation or survival were evaluated for prediction of adult ocean abundance (Winship et al., 2015). While the models demonstrated improved accuracy over models without environmental variables, cross-validation methods (mimicking the assessment timing requirements) did not consistently identify a one-year forecast model that included environmental variables as the best performer. Simpler autoregressive models based on jack returns had similar or better performance (Winship et al., 2015). These results highlight the importance of model validation in developing recruitment-prediction models.

Sibling models may not be a valid means to estimate the abundance of salmon at sea for species with a shorter marine residence period, such as pink salmon (*Oncorhynchus gorbuscha*) and coho salmon, as there are few fish that return early to serve as the basis for estimating the remaining cohort strength. Spawner-recruit relationships have been used to estimate abundance at sea for a number of pink salmon populations. However, escapement (i.e., spawner abundance) surveys can be imprecise. Marine environmental indicators have been investigated as a mechanism for improving the recruitment estimates. However, forecast models across 43 stocks of pink salmon in the states of Washington and Alaska suggest that recruitment estimates including SST benefited only a few stocks (21%) (Haeseker et al., 2005). In recent years, pink salmon abundance in Southeast Alaska has been estimated using ocean survey estimates of juvenile abundance and biophysical indicators (e.g., zooplankton abundance, local physical conditions, and basin-scale indicators) (Wertheimer et al., 2017). While model validation suggests

that models with biophysical indicators are an improvement over those without them, the best performing biophysical model has varied between cohorts, potentially indicating varying processes affecting early marine survival. Estimates of ocean abundance of Oregon coast natural coho salmon attempt to account for cohort-specific processes affecting survival and recruitment by using an ensemble modeling approach. The ensemble model includes six models with nine marine environmental variables indicating basin conditions, low frequency variability, and regional environmental characteristics (Pacific Fishery Management Council (PFMC, 2018)). Cross-validation has demonstrated that the ensemble approach is superior to any individual model.

The application of MSE for salmon has been uncommon. Winship et al. (2013) used an MSE approach considering strategies for reducing fishing mortality on a protected salmon population from Sacramento River, California but did not include environmental covariates. This lack of examples is, in part, due to the complex biological and environmental interactions affecting salmon through their life cycle. The practice of hatchery supplementation can also be seen as a hindrance to conducting MSEs for salmon because hatchery fish alter links between stock size and recruitment. Life-cycle modelling may offer a way to realistically model processes affecting salmon survival during their life cycle and the interactions and feedbacks of the processes (see Gosselin et al., 2018). Currently, along the U.S. west coast, life-cycle models inclusive of environmental factors are well parameterized for the early life stages in freshwater (e.g., Hendrix et al., 2014). These partial life-cycle models have informed temperature-dependent incubation survival, flow release dynamics, and habitat restoration alternatives (Martin et al., 2017; Dudley, 2018). Upon completion and integration of marine components (e.g., Fiechter et al., 2015; Henderson et al., 2018), these models will be important tools for conducting MSEs across the full life cycle including the evaluation of potential mitigation efforts for climate change effects, improved habitats, and managed fisheries.

3. The need for more realistic assessment, harvest, and implementation modules

During the past two decades, many studies have attempted to address questions regarding improved yield or stock conservation via incorporating environmental factors into forecasts. Several studies essentially repeat the approach of Basson (1999), simulating the true population dynamics data with observation error before estimating future catches (e.g., Brunel et al., 2010; Hurtado-Ferro et al., 2010). Basson (1999) acknowledged that this “short-cut” simulation needs to be more realistic; ideally, one would use MSE to simulate the entire procedure.

In a full MSE, data are simulated, an assessment is performed to determine stock status, a HCR is applied to forecast catch, and the procedure is repeated through time to provide a feedback loop (e.g., Aömar et al., 2009a, b; Hurtado-Ferro et al., 2010; Ianelli et al., 2011; Punt, 2011; Punt et al., 2013; Szuwalski and Punt, 2012). Of the studies reviewed, full MSEs were less common than HCR evaluations without the full feedback loop, largely due to computational demands (Punt et al., 2016). While simulation studies reflect a continuum of simple to complex, studies fell into two main categories: 1) those that evaluate existing and alternative HCRs for a particular or hypothetical stock (e.g., Agnew et al., 2002; Ianelli et al., 2011; Punt, 2011; Skagen et al., 2013) and 2) those making forecasts with and without hypothetical climate scenarios to demonstrate different stock trajectories (e.g., Hare et al., 2010; MacKenzie et al., 2012; Mueter et al., 2011; Wilderbuer et al., 2013). None of the reviewed studies incorporates the uncertainty of management implementation, i.e., the inability to achieve management targets precisely even though implementation uncertainty is prevalent in many fisheries. Also, many of the forecast-only studies simply used assessment output without propagating the uncertainty and correlation of those model estimates into their forecasts, thereby underestimating overall uncertainty and potentially introducing bias.

Introducing environment-recruitment uncertainty into the forecast when it was not included in the stock assessment is also suspect.

Several recent studies feature greater biological complexity, testing a range of potential environmental linkages and evaluating whether forecasts improve when accounting for future environmental state (Tables 2 and 3). Most forecast validations fit the model to a subset of available data and predict the remaining years so that forecasts are compared with observations. For example, Winship et al. (2015) evaluates the predictability of the Sacramento Index (a proxy for adult Chinook salmon abundance) by testing various functional relationships with explicit terms for environmental variables (SST, wind speed and stress, and other oceanographic measures) or with flexible models that allowed for smooth changes, reflecting low-frequency environmental or ecological variation. A greater emphasis on this type of validation is warranted in future work and could help reduce the frequency of false positives that lead to acceptance of environmental drivers, which are then dropped after one or more years of additional data are considered.

Selection of fishes to a fishery often occurs at a young age, typically less than age two; therefore, when a study explicitly investigates relationships between recruitment and the environment, the time scale was either contemporaneous (no lag) or at most with a one-year lag. For example, Mackenzie et al. (2008) evaluated whether incorporating the North Atlantic Oscillation index value from the same year as the assessment would improve the assessment estimate of age-1 fish that year. An exception to the time scale of lags investigated would be the MSE of Punt (2011), where an environmental driver was incorporated by simulating recruitment data that were linked to the timing of spring transition three years prior, although the assessment component of the MSE did not attempt to account for the environment. None of the reviewed studies investigated multiple lags that could occur with skipped spawning or recruitment at older ages, though Deyle et al. (2013) noted that multivariate state-space models have the potential to include multiple lags if supported by the data.

The complexity of interactions that could occur in the early life-history stages prior to recruitment make it difficult to derive explicit mechanistic models of how the environment directly affects survival. Furthermore, long time series of data for hypothesized drivers that span sufficient contrast in spawner abundance are rare. Perhaps this is why a majority of studies incorporate the environment implicitly by allowing reference points in HCRs to reflect recent years of recruitment and biological parameters (e.g., the “dynamic B0”, MacCall et al., 1985) or by basing forecasts of recruitment on a recent time period rather than the full time series (A’mar et al., 2009a, Ianelli et al., 2011; Punt et al., 2013; Skagen et al., 2013). Using recent recruitment and biological parameters makes the implicit assumption that the near-term environmental state, and its effect on stock dynamics, will be similar to recent observations, without the burden of predicting the environmental state and estimating the functional relationship with recruitment.

Another challenge to developing direct or lagged empirical environment-recruitment relationships is the lack of recruitment observations. Surveys of age-0 and age-1 fish are uncommon (for exceptions see Vaughan et al., 2011; ICES, 2013), and thus, most studies investigate relationships using stock assessment output that should be interpreted with extreme caution (Brooks and Deroba, 2015). When explicit versus implicit incorporation of the environment has been compared, implicitly including the environment through autocorrelation in recruitment or modelling smooth trends over time appears less prone to prediction error (Punt, 2011; Winship et al., 2015; Johnson et al., 2016a). At least one study found an improvement in forecast performance by explicitly including the environment (Agnew et al., 2002), but this was for a simplistic simulation of an annual life cycle (squid). Future work should be vetted using simulation prior to being implemented with stock assessment output (e.g., Deyle et al., 2013) or ideally should be included in the stock assessment itself (e.g., A’mar et al., 2009b).

No single study performed a full factorial design using a range of

Table 2
Summary of environmental covariates considered and used for forecasting, simulations, or MSEs.

Publication	Covariates Considered	N Considered	Selected	N Selected	Used to Forecast	N Forecast
Forecasting					A principle components from all variables	Principle Components
Burke et al., 2013	Pacific Decadal Oscillation (PDO), Oceanic Nino Index, SST, Spring transition, Upwelling strength, Upwelling length, Deep temperature, Deep salinity, Freshwater flow, Freshwater temperature, Copepod richness and northern anomaly, Copepod community, Biological spring transition, Ichthyoplankton biomass, Ichthyoplankton community index score, Chinook diet (May, June), Chinook condition (May), Chinook Growth (June), Copepod community index score from vertical nets, June biomass of bongo samples, Density of age 1 anchovy, Density of adult hake, Prevalence of <i>Renibacterium salmoninarum</i> , June Chinook survey CPUE, June and July Salmon CPUE in Vancouver	23	All	23		
Deyle et al., 2013	Scripts Institute of Oceanography (SIO) Temperature (surface and bottom), North Pacific Index (NPI), Newport Pier SST, PDO, North Pacific Gyre Oscillation (NPGO), Southern Oscillation Index (SOI), Multivariate El Niño Index (MEI), and Southern California Bight (SCB) SST Summer SST Northeast Pacific regional	9	SIO SST, PDO	2	SIO SST and PDO, one at a time	1
Haeseker et al., 2005	Minimum winter air temperature	1	Summer SST	1	SST	1
Hare et al., 2010	2 models, 1. predator abundance (cod), prey abundance (Caplin); 2. hatch date, SST, proportion of repeat spawners, and predator abundance (young saithe)	6	Minimum winter air temperature NA	1 NA	Minimum winter air temperature NA	1 NA
Logerwell et al., 2003	NPI, Upwelling intensity, SST, Spring transition date, sea level (all treated seasonally during emigration and some during the first year at sea).	10	SST during winter prior to emigration, Spring transition date during emigration, Sea level during emigration, SST during winter following emigration Each fit in turn as an example	4	SST during winter prior to emigration, Spring transition date during emigration, Sea level during emigration, SST during winter following emigration Jan-Feb NAO	4
Mackenzie et al., 2008	May water temperature, NAO (Jan-Feb), and ice cover (Baltic sea)	3	All	3, but one at a time	Four sets of ocean model temperature projections	1 at a time
Mackenzie et al., 2012	Modeled August temperature from three Baltic Sea ocean-biogeochemical hind cast models, and observed May temperature	4	PC 1 (average temperature), and PC 3 (predation pressure)	4, but one at a time	SST	1
Mueter et al., 2011	Ice retreat, Spring transition date, Summer SST, Summer winds, Stratification, Predation, and Principle components (PCs) 1 through 4 from the above covariates	10	May-July PDO (y = 4 year average), Summer UWI, Fall NPGO, SPR, Log Spawners, Fall MEI, Winter NPI, Spring	2	SPR, log spawners, Fall MEI, Summer UWI, Spring SST, Spring SSH, Fall UWI, January SST	8 covariates across 6 models with 3 variables each. This study uses model averaging to address uncertainty
Rupp et al., 2012	Seasonal running averages for MEI, NPGO, NPI, Oceanic Nino Index (ONI), PDO, Spring Transition Date (SPR), Sea Surface Height, SST and Upwelling Wind Index (UWI). Calculated 3 month (2 month for	> 100		12 variables across 18 selected models		

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Table 2 (continued)

	Publication	Covariates Considered	N Considered	Selected	N Selected	Used to Forecast	N Forecast
		MEI) running means to get 12 time series for each variable. Additionally, Dec-Jan means for all but MEI, and January means. Log Spawners.		SST, winter ONI, spring SSH, Fall UWI, January SST			
	Pacific Fishery Management Council (PFMC), 2018	Mean May-Jul PDO averaged over 4 years prior return year, MEI Oct-Dec the year prior return, Spring Transition the year prior return, Sea Surface Height Apr-Jun the year prior return, Upwelling Jul-Sep and Sep-Nov the year prior return, SST May-Jul the year prior return and Jan the year of return, Log Spawners 3 years prior return	9	Ensemble mean predictor	9	Mean May-Jul PDO averaged over 4 years prior return year, MEI Oct-Dec the year prior return, Spring Transition the year prior return, Sea Surface Height Apr-Jun the year prior return, Upwelling Jul-Sep and Sep-Nov the year prior return, SST May-Jul the year prior return and Jan the year of return, log Spawners 3 years prior return	Ensemble of 6 models inclusive of three variables each
	Vaughan et al., 2011	Mississippi River discharge	1	Mississippi River discharge	1	Mississippi River discharge	1
	Ward et al., 2014 Wertheimer et al., 2017	NA Salmon harvest and biophysical variables; Juvenile salmon survey CPUE; Juvenile condition; Predators abundance; Zooplankton; Local-scale physics (water temperature, mixed layer depth); Basin-scale physics (PDO, NPI, MEI, NPGO); Ecosystem Ranks Index	NA 22	NA Juvenile CPUE or Ecosystem Ranks Index. Additional biophysical covariates are chosen through model selection.	NA Varies inter-annually	NA Juvenile CPUE or Ecosystem Ranks Index. Additional biophysical covariates are chosen through model selection.	NA Varies inter-annually
	Wilderbuer et al., 2013	Ending drift depth, Ending drift distance from land, Average Annual Arctic Oscillation (AO), May SST, Spring wind direction, and Spawning stock size	6 main effects and 5 interactions, 11 total	Spring wind direction and stock size (northern rock sole); AO, Spring wind direction, and Stock size (arrowtooth flounder); Stock size (flathead sole)	1 to 3, depending on the stock	Spring wind direction	1
	Winship et al., 2015	3 seasonal values for: SST, Wind speed, Northerly wind stress, Easterly wind stress, Wind curl, Upwelling Index, Sea level and Spring transition index. Also, Jack spawning escapement	22	NA, Many models evaluated.	22	22	6 total: 4 models with Jacks, and 2 models with environmental covariates each
MSE / Simulation/ Reference Points / HCRs	Agnew et al., 2002 A'mar et al., 2009a A'mar et al., 2009b Brooks, 2013 Brunel et al., 2010	SST Two theoretical regime changes based on observed frequency Winter Precipitation, Winter Wind Mixing Energy (WME), Spring eddy formation, Spring WME, Spring Upwelling, Spring Temperature, Spring Precipitation, Summer WME, Summer SST, Fall SST Theoretical good or bad environment Simulation assumes relationship know without error. Models were fit with historical data and selected using AIC. Covariates: NOAA, temperature, salinity (various measures)	1 1 at a time 10 2, one at a time Not Clear, < 10	SST Two theoretical regime changes based on observed frequency Seasonal IPCC model outputs for: precipitation, WME, and advection of ocean water NA Jan-June temperature (Cod); NOAA lagged 2 years, feeding ground temperature lagged 1 year, spawning ground minimum	1 1 at a time 12 NA 1.3,1	SST Two theoretical regime changes based on observed frequency Seasonal IPCC mode outputs for: precipitation, WME, and advection of ocean water NA Scenario where the range of environmental variation is similar to historical observations. 4 Scenarios: constant trend with no	1 1 at a time 12 each from 6 downscaled IPCC models (72 total) NA 4, each in turn

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Table 2 (continued)

Publication	Covariates Considered	N Considered	Selected	N Selected	Used to Forecast	N Forecast
Haltuch and Punt, 2011	Two theoretical cyclical trends (sine and step function) with 25 year period	2, 1 at a time	temperature lagged 1 year (Plaice); Spawning ground salinity lagged 1 year (Herring) NA	NA	variability, random trend, upward directional with variability, downward directional with variability Two theoretical cyclical trends (sine and step function) with 25 year period and two time periods (25 and 50 years) SST was simulated by randomizing historical data. SST from 3 IPCC emissions scenarios (82 time series)	4, each in turn
Hurtado et al., 2010	SST, two sources	1 at a time	NA	NA		2, each in turn
Ianelli et al., 2011	Ice retreat, Spring transition date, Summer SST, Summer winds, Stratification, Predation, and Principle components (PCs) 1 through 4 from the above covariates	10	PC1, PC3	2		1
Punt, 2011	The date of spring transition (no trend, plus 3 differing trends), temporal autocorrelation	5, one at a time	The date of spring transition (no trend, plus 3 differing trends), temporal autocorrelation NA	5	The date of spring transition (no trend, plus 3 differing trends), temporal autocorrelation Future recruitment is generated sampling past recruitments allowing for trends including: No change, linear increase, linear decrease, and 2 levels of average future recruitment NA	5, one at a time
Punt et al., 2013	NA	1 at a time	NA	NA	5 scenarios, each in turn	
Punt et al., 2014	Change point detection in stock-recruit time series	NA	NA	NA	NA	NA
Skagen et al., 2013	General environmental drivers represented as an asymmetric bell shaped function	NA	NA	NA	NA	NA
Szuwalski and Punt, 2012	Average recruitment (based on observations) with recruitment shifts recruitment at specified years, intervals, or oscillating control (based on PDO)	NA	NA	NA	NA	Average recruitment with recruitment shifts recruitment at specified years, intervals, or oscillating control

Table 3
Summary of simulated stock-recruitment relationships used in the operating model (OM), the estimation method (EM), and the forecasted dynamics (Forecast) for the reviewed studies.

Publication	Model type	OM	EM	Forecast
Forecasting				
Burke et al., 2013	Principle component regression and maximum covariance analysis		$\ln(R_y) = b(PC1) + a$	Principle component regression and maximum covariance analysis using 31 variables.
Doyle et al., 2013	Multivariate state space reconstruction	Estimability checked using $R_y = SSB_{y-1}e^{(r+y-1)(1-SSB_{y-1})}e^{\psi Y_{y-1}}$ and multispecies Ricker	Lagged SSB and T	Lagged SSB and T
Haeseker et al., 2005	Sibling model approaches with and without AR terms. Linearized Ricker stock recruitment with and with environmental covariates.			
Hare et al., 2010	Age-structured dynamics with estuarine-T driven over-winter R mortality		$R_y = SSB_{y-1}e^{(a-bSSB_{y-1}+cT_y+y)}$	Same as EM
ICES, 2013	VPA			
Logerwell et al., 2003	Generalized additive model		Survey of age-0; combing survey of age-0 and T was suggested but not used in the SA Early coho salmon survival is the response and environmental covariates are added sequentially. Best model is chosen with AIC. Age-1 survey	GM of age-0 abundance 1988–2009
Mackenzie et al., 2008	XSA			(a) GM 1991–2005, (b) regression between $\ln(R)$ and NAOJF, (c) variance-weighted average of the $\ln(R)_{1991-2005}$ and (b), or (d) R if NAO in 2006 and 2007 were the lower or upper 10th%ile of the NAOJF for 1973–2005 Age-structured model w/ age-1 $R = 0.178SSB_{y-0.001SSB_{y+0.396T}}$
Mackenzie et al., 2012	R was estimated from SA and used as $\ln(R)$ in EM as data		Linear & non-linear (Ricker & BH) models of \hat{R} w/ T were explored, forecasts use best model	
Mueter et al., 2011			(a) Non-linear model of residuals from $R_y = \frac{SSB_{y-1}}{\varnothing_0} e^{\alpha(1-\frac{SSB_{y-1}}{SSB_0})} e^{\beta Y} + 1\text{-year lagged } V$ covariates; (b) $\ln(\hat{R}_y) = \alpha + \beta SSB_{y-1} + \sum_i \gamma_i V_{i,y-1} + \ln(SSB_{y-1}) + \varepsilon_y$ $\hat{Y} = f(X_1) + f(X_2) + f(X_3) + \varepsilon$ Y is the log-transformation of annual recruit abundance, X_1 through X_3 are the predictor variables, ε is the deviation of \hat{Y} from Y .	Age-structured model with age-1 projected using (1) Normally distributed residuals from SR relationship used to compute residuals in (a), (2) best model found in (a) w/ uncertainty, or (3) best model found in (b) w/ uncertainty The geometric mean of the six generalized additive model predictors is used as an estimate of recruit abundance. Ensemble approach of 2 and 3 variable models.
Pacific Fishery Management Council (PFMC), 2018	6 generalized additive models with 3 covariates and coho salmon abundance as dependent variable		$R_y = f(SSB_{y-1}h, R_0)e^{\beta Y_y}$, where f is either a Ricker or BH, β is fixed at zero or estimated, and h is fixed at ∞ or 1, respectively.	
Rupp et al., 2012	Generalized additive model with recruits as dependent variable		$\ln(R_y) = f(X1) + f(X2) + f(X3)$	
Vaughan et al., 2011	Age-structured SA model fit to survey data that includes age-0			$R_{y+1} = b_0 + b_1(F_y - F_{y-1}) + b_2R_t + \varepsilon_t$
Ward et al., 2014	Forecasts using time-series data on abundance			ARIMA, regression, and non-parametric models
Wertheimer et al., 2017	Backward/forward stepwise regression		Harvest = $\alpha + \beta(Y) + \gamma_1X_1 + \dots + \gamma_nX_n + \varepsilon$; Y is either CPUE or Ecosystem Ranks Index, X is biophysical covariate	1. Developed regression model with CPUE or Ecosystem Ranks Index and additional physical conditions, zooplankton measures, adult coho abundance, pink salmon condition; 2. Calculate AICc to evaluate over parameterization; 3. On remaining models, use a jackknife procedure to estimate forecast error; 4. Select best model.

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Table 3 (continued)

Publication	Model type	OM	EM	Forecast
Wilderbuer et al., 2013	Used estimates of recruitment from an age-structured SA model as data		$R = \alpha SSB_y - \beta SSB_y + E_1 V_1 + \dots + E_7 V_7$	Age-structured model w/ R model w/ lowest AIC from EM
Winship et al., 2015	Sum of ocean, river, & escapement was used as point-estimate data			13 models (linear, log-linear, and non-linear) to predict adult ocean salmon abundance from jack abundance & Vs in $y-1$
MSE / Simulation /Reference Points / HCRs				
Agnew et al., 2002	Numbers model with linear growth	(a) $R \sim N(2736, 1724)$ or (b) $R \sim N(15332 - 2189T, \sigma_T)$	$R = 15332 - 2189T$	
A'mar et al., 2009a	Age-structured w/o SR relationship	Lognormally distributed about a mean that varies w/ regimes	Lognormally distributed about a mean, where each EMs varied in the amount of "regime" information that was available Lognormally distributed about a mean	
A'mar et al., 2009b	Age-structured w/o SR relationship	$R_y = R_0 \sum_{i=1}^n (V_{i,y-1}) e^{(\phi_y - 1 - \frac{\sigma_y^2}{2})}$		
Brooks, 2013	Calculation of reference points based on spawning potential ratio	(a) variability in slope at the origin and (b) unexploited SSB per R	Parameterized SR function in terms of lifetime maximum production of recruits	
Brunel et al., 2010	Age-structured dynamics of North Sea herring, plaice, or cod	Segmented regression (herring) and Ricker (cod and plaice) both w/ GAMs for R-V relationship $R_y = \int_{SR} (SSB_{y-1}) f_r (V_{y-1}, \dots) + \epsilon_y$	No SA was estimated and instead $SSB_y \sim N(True SSB_y, \sigma)$ and the information used to calculate F varied but last 8 years of V determined median value for 1 of 3 HCRs (a) Empirical measurements of SSB and R w/ noise or (b) SA with 3 alternative BH SR functions (1) externally estimated w/ SA output, (2) internal estimation but ignore V, and (3) internal estimation w/ V known w/o error; SSB_0 is calculated from different time periods	
Haltuch and Punt, 2011	Age-structured w/ and w/o a SR relationship that can be influenced by the environment	BH w/ environment: $R_y = \frac{4hR_0 SSB_y}{(1-h)SSB_y + (5h-1)SSB_y} e^{f(0.1)V_{y-1} \phi_y - \frac{\sigma_y^2}{2}}$, where SSB is SSB corresponding to deterministic unfished recruitment Generalized Ricker: $\frac{R}{SSB} = \alpha + \beta SSB + \gamma T + \epsilon$	$SSB_y = SSB_y e^{\epsilon_y}$, $\hat{R}_y = R_y e^{\epsilon_y}$, and V_y was known w/o error	
Hurtado et al., 2010	Age-structured w/ Ricker SR function and w/ and w/o O V effects using probabilistic regime shifts			
Ianelli et al., 2011	Age-structured forward projections	R generated using either (a) inverse Gaussian or (b) $e^{0.7886 - 1.7637 - 0.6626T^2} e^{d_{i,y}}$	SA every 4 th year, that includes a BH SR function: $R_y = \frac{SSB_{y-3} e^{\beta S_{y-1} + 1} \sqrt{1 - \rho^2} \sigma_y}{\alpha + \beta SSB_{y-3}}$	(a) sampling at random from past R or (b) estimated using a relationship between R and V
Punt, 2011	Age- and sex-structured model	R is (a) $\ln(R_y) = b_0 + \rho \phi_{y-1} + \epsilon_y$ or (b) $\ln(R_y) = c_0 + c_1 V_y + \epsilon_y$, where $V_y = e^{d_0 d_1^y - 200T_y}$ if $y > 2007$	Lognormally distributed about a time-invariant mean	Average future recruitment is either based on (a) last five years or (b) last ten years
Punt et al., 2013	Size- and sex-structured model w/o a SR relationship	(a) no change, (b) linear increase, or (c) linear decrease	(a) BH, (b) Ricker, and (c) linear; steepness and R_0 were fixed &/or estimated with $F_{MSY} = F_{35\%}$ in (a) & (b); (a)-(c) were estimated w/ and w/o change points	
Punt et al., 2014	Fitting SR function to estimates of R and mature male biomass from SA models			
Skagen et al., 2013	Length- and age-based model with super individuals comprised of multiple individuals	BH $R_y = \frac{\alpha SSB_y}{SSB_y + b} \phi_y$, where a can be affected by the environment through a logistic- or bell-shaped function (a) BH w/ steepness set such that $F_{MSY} = F_{35\%}$ w/ bias-corrected lognormal error, (b) shift between "high" and "low" recruitment every 10 years with bias-corrected lognormal error and means equal to those observed in each regime, and (c) oscillating dynamics between (a) and (b) based on V w/ a cap of 3 million R	(a) $\hat{R}_y = R_y e^{\epsilon_y}$ and other population parameters or (b) V	HCR is dependent on (a) average estimated recruitment for 1979–present or (b) regime status, where mean R dependent on information from the current regime
Szuwalski and Punt, 2012	Size- and sex-based model			

assumptions about error distribution (e.g., lognormal or normal truncated and uncorrelated or serially correlated) and form of the stock-recruit relationship (e.g., compensatory or over-compensatory) in both the simulated dynamics and the estimation method. Instead, a single set of assumptions was typically used to fit data simulated from a Beverton-Holt stock-recruit function (Beverton and Holt, 1957; e.g., Haltuch and Punt, 2011) or a single Beverton-Holt estimation method fit to recruitment simulated using environmentally driven, autoregressive functions (e.g., Punt, 2011). Although simulation studies that utilize the “self-test” (i.e., a single model is used to simulate and estimate) are useful, future studies should investigate scenarios highlighting “cross-tests” to ensure that proposed models are robust to misspecification. Furthermore, the majority of the dynamics investigated in simulations concerning the environment occurred in the data-generating phase rather than in the estimation phase (Table 3; for an exception see Haltuch and Punt, 2011).

4. Evaluating the implementation of univariate versus multi-life stage mechanistic drivers, historical data availability, spatial scale, and temporal forecast scale

Mechanistic explanations for the environmental drivers chosen in the reviewed studies are often based upon a strong foundation of previously published literature (e.g., MacKenzie et al., 2008; Mueter et al., 2011; Tommasi et al., 2017a) or implement theoretical environmental drivers based on observed patterns of environmental variation (e.g., A'mar et al., 2009a; Hurtado-Ferro et al., 2010; Haltuch and Punt, 2011). Two notable exceptions are for opportunistic species that grow and mature quickly, the time-series analyses of Pacific sardine presented by Deyle et al. (2013) and the squid MSE by Agnew et al. (2002). While the methods applied to Pacific sardine (Deyle et al., 2013) do not require mechanistic assumptions, there is an extensive body of literature regarding environmental drivers of Pacific sardine recruitment. A majority of the MSEs implement theoretical univariate environmental time series that are based on observed environmental data (for example, shifts among environmental conditions driving high and low recruitment states) but do not implement a single mechanistic driver (Table 2).

The number of environmental covariates evaluated, and selection criteria, varied among studies. In general, relatively few environmental covariates were considered, with an increasing trend toward using model selection to choose covariates. While two forecasting studies considered only a single covariate based on the results of previously published work (Hare et al., 2010; Vaughan et al., 2011), most used model selection to identify important covariates out of less than 10 environmental covariates. Only one study evaluated more than 20 environmental covariates; eight were examined, of which seven were evaluated seasonally (Winship et al., 2015; Table 2). Winship et al. (2015) conducted cross-validation on a suite of models with and without environmental variables. They found that the best environmental model varied over time and depended on the performance metric used; overall, the simpler models performed as well or better than environmental models. The MSE and simulation studies generally investigated just one or two environmental covariates and did not conduct model selection, but many relationships were based on published mechanistic research (e.g., Ianelli et al., 2011). A'mar et al. (2009b) and Brunel et al. (2010) are two exceptions to the above, including model selection prior to implementing MSEs. While many of the forecasting and some of the MSE and simulation studies considered multiple covariates, most used a single covariate to forecast recruitment. A few studies also used the scores from the first dimension from a multivariate data reduction as a covariate to alleviate issues of covariability among environmental variables (Burke et al., 2013; Winship et al., 2015).

The sources of uncertainty considered in forecasts depended on the type of study and the method of modeling the environmental driver.

Most MSE and simulation studies implement a general environment-recruitment relationship as regime shifts or change point detection based on observed variation in environmental data (A'mar et al., 2009a; Hurtado-Ferro et al., 2010; Haltuch and Punt, 2011; Szuwalski and Punt, 2012; Brooks, 2013; Punt et al., 2014) or investigate the implications of trends or autocorrelation in a single index (Brunel et al., 2010; Punt, 2011; Table 2). Forecasts from the MSE and simulation studies generally captured a wider range of uncertainty in future environmental conditions than the forecast-only studies, as they were conducted with multiple IPCC models or emissions scenarios, down-scaled models, or multiple future theoretical scenarios (A'mar et al., 2009a,b; Brunel et al., 2010; Haltuch and Punt, 2011; Hurtado-Ferro et al., 2010; Ianelli et al., 2011; Punt, 2011; Punt et al., 2013; Szuwalski and Punt, 2012). The more complex analyses probably reflect uncertainty that is more realistic; in some cases, even model uncertainty is incorporated.

Both recruitment estimates and environmental-driver data were used at regional spatial scales, with a few studies also considering basin-scale environmental indices such as El Niño-Southern Oscillation (ENSO) Index or the Pacific Decadal Oscillation (e.g., Mackenzie et al., 2008; Deyle et al., 2013; Table 2). No studies considered environmental covariates at large spatial scales alone. Several forecasting studies used covariates based on the output of IPCC-class global climate models (Hare et al., 2010; MacKenzie et al., 2012; Wilderbuer et al., 2013), projecting environmental conditions forward on multi-decadal time scales. Regional metrics of temperature (e.g., Deyle et al., 2013) were the most frequently considered and selected covariates, via model selection based on previous studies, and were the covariate most frequently used to conduct forecasts, simulations, and MSEs. There were several approaches taken to forecast temperature, e.g., resampling from historic time series (e.g., Brunel et al., 2010; Hurtado-Ferro et al., 2010; Ianelli et al., 2011) or using multiple climate models such as those generated by the IPCC (Hare et al., 2010) or other regionally down-scaled ocean biogeochemical models (MacKenzie et al., 2012).

Most studies had a minimum of 25 to 30 years of historical data available to derive forecast scenarios, or to parameterize simulations and MSEs with recruitment-environment relationships, but a few had even longer time series (e.g., MacKenzie et al., 2012; Table 2). The forecast-only studies produced forecasts ranging from near term, with Vaughan et al. (2011) producing annual forecasts and Mackenzie et al. (2008) producing annual and five-year forecasts, to long term, with about half of the studies forecasting through 2050 or 2100 (e.g., Hare et al., 2010; Mueter et al., 2011; Mackenzie et al., 2012). All of the MSE and simulation studies that produced forecasts did so on longer time scales, ranging from 25 to 80 years, with the exception of the Agnew et al. (2002) MSE that uses less than 20 years of data and produces one-year ahead forecasts for short-lived squid. Long-term predictions are necessary to fully evaluate the effects of management in MSEs given that even for life histories with short lifespans (e.g., 3–4 years) environmental effects on this year's recruitment may not be fully realized until their spawning potential is realized, or not. Also, several studies with long-term predictions characterized the forecasts as “through the 21st century” (Hare et al., 2010; MacKenzie et al., 2012), so the specification of the forecast horizon was more likely to characterize potential changes this century and stimulate strategic planning, rather than the year 2100 having a direct management link.

5. Successes

This review broadly summarizes advances in the application of recruitment-environment relationships in single-species forecasts, parameterization of simulations, and MSEs from the year 2000 through 2017. We found that for species with recruitment-dominated population dynamics and strong environmental-recruitment drivers, management may benefit from the use of environmental factors. Collectively, these studies encompass a wide range of species and life-history types,

including invertebrates; anadromous and coastal pelagic fishes; and gadiforms, pleuronectiforms, and other groundfishes. Most studies reflect the use of increasingly long time series of historical records, on the order of 25–80 years of data. Clearly, long-term data sets have yielded the longer time series necessary to identify and test robust recruitment–environment relationships (Haltuch and Punt, 2011), underscoring the importance of maintaining continued data collection. While forecast lengths tended to be either near-term (zero to five years) or long-term projections (20 to 80 years), there was a lack of peer-review, published medium-term studies (~5 to 20 years). Such medium-term forecasts have most likely received less attention as they fall between the short-term quota- and assessment-focused questions of tactical stock management and the long-term, strategic questions of climate change. The need for both short- and long-term predictions of environmental variables has been recognized and such forecasts are being developed (e.g., Stock et al., 2011; Tommasi et al., 2017b). Furthermore, it is only recently that oceanographic forecast models have started to show predictive skill on the decadal (1–10 years) scale, and even today this skill is limited to certain parts of the global ocean (e.g., the North Atlantic) (Meehl et al., 2014; Yeager and Robson, 2017). Nevertheless, it seems likely that this time-scale will receive more attention in the future (Payne et al., 2017).

The most clear cases where the use of recruitment–environment relationships were likely to impact fishery management were for species with a short pre-recruit survival window (e.g., opportunistic life-history strategy), where the abbreviated life span made it easier to identify one or a limited set of key drivers of recruitment dynamics. Of the 12 reviewed studies of opportunistic strategists, nine found improvements in predicting recruitment when including an environmental driver. Short-term forecasts for opportunistic species such as sprat, Gulf menhaden, and squid show some skill, along with evidence that these species can benefit from environmentally based HCRs (Agnew et al., 2002; Hurtado-Ferro et al., 2010; Tommasi et al., 2017a). Long-term management gains, without short-term gains, were realized by using an environmentally based F (squid) and a change in reference points at an environmental threshold (Pacific sardine). Setting an environmental or stock biomass threshold level where management strategies change may be sufficient to respond to climate-induced changes in recruitment (Hurtado-Ferro et al., 2010; A'mar et al., 2009a, b; Punt et al., 2013). Implementing HCRs with environmental thresholds would avoid problems arising from environment–recruitment relationships that weaken, break down, or change, as may occur with the addition of new data that are outside the historically observed ranges (Agnew et al., 2002; Brunel et al., 2010; Ianelli et al., 2011; Punt et al., 2013). The evidence is less clear that incorporating environmental thresholds for strong recruitment drivers into management strategies could be successful for periodic strategists, which are longer lived and have low recruitment variability (Basson, 1999; De Oliveira and Butterworth, 2005; A'mar et al., 2009a, 2009b; Brunel et al., 2010; Ianelli et al., 2011). For this life-history, factors such as growth and mortality could play a more important role than recruitment in determining suitable exploitation rates (Payne et al., 2017). However, there are a few cases where some improvement to fishery management of periodic and salmonid strategists was reported from considering environmental drivers of recruitment (e.g., Pacific Fishery Management Council (PFMC, 2018)).

Management systems appear to be responsive to incorporating observed changes in biological parameters, even if the mechanism producing those changes is unknown (e.g., NEFSC, 2012; 2015, 2017; Johnson et al., 2016b; Stawitz et al., 2016). Many one-to-ten-year forecasts currently use recent biological parameters (e.g., growth, recruitment, productivity, maturity) and recruitment estimates that implicitly integrate environment, allowing for reflection of recent environmental conditions in reference points and HCRs (A'mar et al., 2009b; Ianelli et al., 2011; Punt et al., 2013; Skagen et al., 2013). This implicit accounting for the environment appears to be less error prone than using a direct mechanistic relationship where errors in forecasting

the driver can seriously bias management advice. The challenge is to outperform current management systems. Increasingly longer time series and greater contrast in observations of stock size may gradually clarify the functional form of mechanistic relationships, allowing for improvement beyond the current implicit approach.

As a whole, these studies feature well-researched mechanistic drivers of recruitment (e.g., Agnew et al., 2002; A'mar et al., 2009a, b; Punt, 2011; Tommasi et al., 2017a), using model selection to identify a limited set of covariates, representing a trend towards increased understanding of complex processes. This increasingly mechanistic research has resulted in the more frequent use of regional environmental data rather than large spatial scale climate indices (e.g., NAO or PDO), indicating a shift towards identifying more spatio-temporally appropriate recruitment–environment relationships (e.g., Brunel et al., 2010; Hurtado-Ferro et al., 2010; Ianelli et al., 2011), rather than basin scale climate indices that serve as proxies for regional processes (Stenseth et al., 2003). Where large-scale climate indices were considered, it was always in conjunction with regional covariates. Researchers are increasingly focusing on simulation testing and MSEs to investigate risks and benefits of incorporating environmentally-driven recruitment into fisheries models for management, often using simplified theoretical relationships based on mechanistic research.

Generally, fewer than ten environmental covariates are explored; many MSEs used a single environmental covariate, most frequently a temperature metric. Temperature is usually identified as an important direct mechanistic driver of invertebrate and coastal pelagic species recruitment dynamics. In these cases the use of temperature is likely advantageous. However, for some species it is likely that temperature is serving as an easily obtainable proxy for alternative recruitment processes for which data are more difficult to obtain, particularly as investigations go back further in time. In several studies, environmental factors appear to be acting primarily on egg and larval survival, via either transport of planktonic life stages to suitable nursery areas (Vaughan et al., 2011; Wilderbuer et al., 2013) or environmental conditions within nursery areas (MacKenzie et al., 2008; Hare et al., 2010; MacKenzie et al., 2012). In some cases, multiple environmental factors affected survival of larvae and age-0 juveniles in complex ways (Mueter et al., 2011), suggesting that a series of multiple environmental conditions through time and space are important in determining recruitment strength. While using temperature as a recruitment proxy for species with complex multi-stage early life history processes is a reasonable first step and may be weakly explanatory, more mechanistic studies that move beyond using temperature alone are likely to be more useful in the long term.

6. Challenges

Most reference points and control rules do not explicitly incorporate environmental relationships, yet they often perform similarly or outperform environmentally based relationships (e.g., Punt, 2011). Among the eleven reviewed studies of periodic strategists, only three concluded that incorporating environmental variables improved stock–recruit prediction (Hare et al., 2010; Mueter et al., 2011; Wilderbuer et al., 2013). A common methodological approach in these three studies was the use of output from stock assessment models that was subsequently used to fit environmentally explicit stock–recruit functions. While ideally the above analyses would have used direct recruitment observations, observational data are often not available, resulting in the use of stock assessment model output as the only source of recruitment information. In such cases, considering the uncertainties associated with using stock assessment model estimates, collaborating with assessment scientists, sensitivity analyses, errors-in-variables methods, and cross-validation methods can aid in avoiding spurious results (Brooks and Deroba, 2015). The remaining eight studies, primarily simulation-based studies, generally concluded no improvement in management strategy or forecasting accuracy.

Studies that conducted full MSEs chose environmental factors based on demonstrated mechanistic links (Agnew et al., 2002; A'mar et al., 2009a, b; Punt, 2011) and were included after accounting for the spatial area and temporal period affecting the appropriate life stages (Brunel et al., 2010; Hurtado-Ferro et al., 2010; Ianelli et al., 2011). All studies used indices that covered the range of historical data (Agnew et al., 2002; A'mar et al., 2009a, b; Brunel et al., 2010; Hurtado-Ferro et al., 2010; Haltuch and Punt, 2011; Ianelli et al., 2011) or projected forward using climate models (Ianelli et al., 2011; Punt, 2011). Many studies found that the strength of the environmental relationship was important (Brunel et al., 2010; Agnew et al., 2002; Haltuch and Punt, 2011; Ianelli et al., 2011; Punt et al., 2013), but suggest that relationships may not hold under future climate change as environmental conditions range beyond historical observations (Brunel et al., 2010; Agnew et al., 2002; Ianelli et al., 2011; Punt et al., 2013). In general, including environmental effects in models to generate reference points did not outperform current approaches. Multiple factors likely contribute to these results. Addressing the following challenges, where possible, may lead to the identification of more robust recruitment-environment relationships with greater explanatory power and potentially greater management impacts.

First, while multiple mechanisms can be responsible for the complex interactions between environmental conditions and life-history stages (Planque and Fox, 1998), potentially reducing survival at multiple life stages, this complexity is often greatly simplified when modeled (e.g., Basson, 1999), and therefore, the relationships identified are subject to failure in practice (Myers, 1998). Complex relationships are often reduced from multiple covariates to the mean of a single important factor (often some temperature metric) when applied to management models (Ianelli et al., 2011). The investigation or availability of data for only a few life stages likely contributes to this problem as well, resulting in reduced ability to explain the variation in recruitment and reduced impact on management outcomes. An intermediate step in complexity implemented in many MSE and simulation studies was the specification of regime shifts or change point detection that allowed for shifts between high and low recruitment states. A further step in complexity might be to consider different drivers acting in each recruitment state using methods such as those implemented by Perretti et al. (2013) or Deyle et al. (2016). Species with a longer pre-recruit survival window (e.g., seasonal, or inter-annual) during which the environment could potentially influence recruitment may also benefit from autoregressive forecast methods.

Second, most studies use environmental data as mean values aggregated over space and time, without consideration of uncertainty or spatial and temporal correlation. However, spatio-temporal variability could also be important in determining recruitment strength (e.g., Donahue et al., 2015). Furthermore, autocorrelation has important implications for statistical inference (Pyper and Peterman, 1998) and can increase the probability of falsely identifying relationships (inflated risk of Type-I errors). The *a priori* choice of drivers based on good biological knowledge and understanding of the processes that affect the organism directly is therefore key to avoiding erroneous identification of relationships (Dickey-Collas et al., 2014).

Third, in most cases, it is difficult to observe recruitment, leading to the use of model-generated recruitment estimates for identifying recruitment-environment relationships and projecting recruitment into the future. Typically, model outputs, either recruitment or recruitment deviations, are treated as data, and the uncertainty of the assessment results and the structural assumptions of the model used to generate the output are ignored (Brooks and Deroba, 2015). Given that direct observations of recruitment are not possible for many stocks, results that are more robust may be obtained by 1) testing recruitment-environment relationships using stringent significance thresholds, 2) considering the uncertainty in model derived recruitment and spawning biomass estimates, and 3) simulation testing of recruitment-environment relationships (e.g., Deyle et al., 2013). The best approach would

be to incorporate the environmental driver into the assessment, provided the selection of the environmental driver was based on model selection and validation, and that the uncertainty associated with the environmental driver is reflected (e.g., A'mar et al., 2009b; Miller et al., 2016). However, no matter how strong the environment-recruitment relationship, it will be difficult to make improved recruitment forecasts for long-lived species exhibiting quasi-random recruitment that is not well selected by either a survey or fishery at young ages. Again, in these cases, auto-correlative methods are more promising.

There is a need for transitioning published work that is largely conceptual and research focused to management applications. However, evaluating the direct impact of published studies on management remains difficult as management actions are typically documented in the grey literature (see Skern-Mauritzen et al., 2016). An additional research-to-operations barrier is that none of the reviewed studies incorporates management implementation uncertainty (i.e., the inability to achieve management targets precisely), so reported results may be optimistic for some fisheries. Furthermore, while time series of biological observations continues to increase, these time series may still not be long enough to understand how recruitment-environmental interactions change across different regimes and climate trends, resulting in the disappearance of previously reported relationships. Finally, the studies in this review produce both short- and long-term forecasts and MSEs, but no studies produced environmentally driven medium-term (~5 to 20 years) forecasts or MSEs, which can be a period considered for tactical fisheries management of species with periodic life-history strategies and for rebuilding overfished stocks.

Several recent works (Tommasi et al., 2017b; Payne et al., 2017) have examined the challenges associated with generating ecological forecasts for the management of living marine resources. Similar to this study, these reviews showed that the success of living marine resource forecasting depends upon mechanistic understanding of (in this case) environment-recruitment relationships, long time series of field and laboratory observations, and data collections and analyses that encompass the range of spatial and temporal scales over which climate and living marine resources interact. However, a key factor influencing the success of forecasts not touched on here is a close collaboration with potential end-users, to identify, develop, verify, and refine forecast products (Hobday et al., 2016). In the case of recruitment forecasting, this would require a close collaboration between recruitment scientists, ecological forecasters, and stakeholders to define both useful forecast horizons and the minimum skill level that is required for the forecast to be useful. The MSEs catalogued in this work can provide good examples of how such questions can be addressed. Ultimately, the successful application of such forecast products requires striking a balance between what is feasible and what is useful (Payne et al., 2017).

7. Future research recommendations

As fish stock sizes respond to management actions and/or climate change, there is reason to ask whether historical observations can capture future environmental conditions adequately. Extrapolating relationships beyond the range of observed data is always challenging and further complicated by the potential for non-stationary stock-recruit-environment relationships. Therefore, it remains highly important to continue monitoring programs that will not only make it possible to conduct repeated testing of recruitment-environment relationships but will allow for the estimation of current stock size, status, and recruitment.

In the future, increasing emphasis on climate change and environmental drivers of recruitment in the context of assessment and management advice is likely to continue, particularly given the ongoing interest in practical approaches to implementing Ecosystem Based Fishery Management. Based on our review of advances, approaches, and challenges in applications since Basson (1999), we suggest that the following critical topics, in order of importance within each sub-

section, should be pursued in future recruitment forecasting and MSE work:

7.1. Life-history and mechanistic recruitment drivers

- 1 Development of well-defined mechanistic conceptual models as the foundation for investigations that explore how environment affects survival at each life stage, along with process-oriented research to test hypotheses identified as important during such investigations. The aim of this basic research is to identify strong recruitment-environment relationships.
- 2 Improvement of life-cycle models to consider population sensitivity to anthropogenic and environmental variability as well as life-stage based management alternatives. For example, investigation into when the greatest density-dependence occurs, either before or after the majority of environmentally driven fluctuations in survival.
- 3 Investigation of the role of spatial and temporal autocorrelation in recruitment-environment relationships.
- 4 Consideration of how components of spatial scale and fish metamorphosis interact with recruitment. Metamorphosis can influence mortality during the life cycle (see Geffen et al., 2007) and its timing can be tied to environmental cues. Spatial considerations span a broad range in granularity from fine (on the scale of the individual and its “search space”) to coarse (the latitudinal scale that involves different environmental conditions or ecoregions). Often allied to metamorphosis is the settlement phase, which can involve major shifts in habitat (e.g., pelagic to benthic), prey selection, and mortality (see, e.g., Nash and Geffen, 2012).

7.2. Modeling and recruitment forecasting methods

- 1 Exploration of using real-time oceanographic data and sub-annual skillful oceanographic forecasts and their associated uncertainty, as well as forecasts for a wider range of oceanographic covariates beyond temperature for recruitment now-casting and forecasting.
- 2 Investigation of autoregressive short-term forecasting approaches, using current environmental observations rather than using the assumption of mean recruitment in stock projections.
- 3 Incorporating explicit environmental drivers, and their uncertainty, into assessments rather than working with assessment output.
- 4 Use model ensembles to evaluate the implications of alternative stock-recruit relationships when evaluating environmental drivers, including conducting tests to ensure that proposed models are robust to stock-recruit model misspecification.
- 5 Further exploration of model-free and nonlinear modeling approaches such as empirical dynamic modeling (e.g., Perretti et al., 2013; Deyle et al., 2016), to incorporate environmental drivers and forecast recruitment, along with testing of methodological assumptions.

7.3. Simulation studies and management implementation

- 1 Simulation work to identify the best practices in incorporating environment-recruitment relationships into assessments and HCRs.
- 2 Further MSE testing of environment-recruitment relationships in operating and, in particular, estimation models, and the length of time series needed to fully capture long-term dynamics (e.g., Haltuch and Punt, 2011).
- 3 Translation of the timing of environmental forcing on each cohort into management as that cohort matures into the spawning biomass, potentially through using appropriately lagged environmental variables.

Addressing the above priorities will move fishery science towards the goal of accounting for recruitment-environment relationships in forecasts, simulations, and MSEs that yield robust advice to fishery

managers. As this practice develops, it remains important to communicate lessons learned with respect to management applications and to evaluate management outcomes likely to be captured in the grey literature.

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